ISSN: 2249-7196

IJMRR/Aug. 2022/ Volume 12/Issue 3/109-119

Sudheer Pothuraju/ International Journal of Management Research & Review

Enhancing Educational Outcomes through Data-Driven Decision Making in K–12 Schools

Sudheer Pothuraju[1], Ronda Jones[2]

Teacher & Content Lead, Department of Special Education, Austin Independent School District, Texas, USA[1]

Academy Director, Austin Independent School District, Texas, USA[2]

ABSTRACT

This empirical study investigates the impact of data-driven decision making (DDDM) on educational outcomes in K-12 schools across diverse socioeconomic contexts. Analysis of data from 42 schools implementing structured DDDM protocols revealed significant improvements in student achievement metrics, particularly in mathematics (11.3% increase) and reading comprehension (8.7% increase). Schools with comprehensive teacher training in data interpretation demonstrated more substantial gains compared to those with limited training. Implementation challenges identified include data literacy gaps, time constraints, and technology infrastructure limitations. Using a mixed-methods approach combining quantitative student performance data with qualitative assessments of implementation fidelity, this research provides evidence that systematic DDDM practices positively influence educational outcomes when adequately supported by professional development, administrative commitment, and appropriate technological infrastructure. The findings suggest that targeted investments in data systems and staff capacity building can foster more equitable and effective educational environments, particularly benefiting traditionally underperforming student populations.

Keywords: Data-driven decision making, educational outcomes, K-12 education, implementation fidelity, teacher professional development.

1. INTRODUCTION

The Evolution of Data Use in Educational Settings

The landscape of K-12 education has undergone significant transformation in recent decades, with increasing emphasis on accountability, evidence-based practices, and measurable outcomes. Data-driven decision making (DDDM) has emerged as a cornerstone of educational reform efforts, reflecting a broader societal shift toward leveraging quantitative information for institutional improvement. Historical approaches to educational decision making frequently relied on intuition, experience, and tradition; however, contemporary educational leaders increasingly recognize the value of systematic data collection and analysis for informing practice. The evolution from anecdotal to empirical approaches represents more than merely technological advancement—it signifies a fundamental shift in how educational quality and effectiveness are conceptualized and evaluated. This evolution has been accelerated by policy initiatives emphasizing accountability, including No Child Left Behind and subsequent legislation requiring systematic reporting of student achievement data. Additionally, technological innovations have dramatically reduced barriers to data collection, storage, and analysis, making sophisticated analytical approaches increasingly accessible to school-level administrators and classroom teachers.

Theoretical Foundations of Data-Driven Decision Making

Data-driven decision making in educational contexts draws upon multiple theoretical frameworks, including organizational learning theory, improvement science, and systems thinking. Organizational learning theory suggests that institutions improve through systematic analysis of information, creation of knowledge, and adaptation of practices. In educational settings, this manifests as cyclical processes of gathering student performance data, interpreting results, implementing targeted interventions, and measuring outcomes. Improvement science provides structured methodologies for continuous enhancement through small-scale, iterative changes informed by localized data. Systems thinking emphasizes examining interrelationships between various elements within educational environments—understanding how changes in instructional approaches affect not only academic achievement but also student engagement, attendance, and social-emotional development. These theoretical frameworks collectively provide conceptual underpinnings for DDDM practices, emphasizing that effective implementation requires not merely technological tools but fundamental shifts in organizational culture and professional norms.

Current Challenges and Opportunities in Educational DDDM

Despite growing consensus regarding the potential benefits of data-driven approaches, educational institutions continue to face significant implementation challenges. Data literacy remains inconsistent among educators, with many reporting discomfort interpreting statistical information or translating analytical insights into actionable instructional strategies. Time constraints represent another persistent barrier, as comprehensive data analysis requires dedicated planning time frequently unavailable within typical school schedules. Additionally, technological infrastructure disparities create inequitable access to robust data management systems, particularly affecting schools in economically disadvantaged communities. Alongside these challenges, however, substantial opportunities exist for enhancing educational outcomes through enhanced DDDM practices. Emerging technologies offer increasingly sophisticated analytical capabilities, including predictive analytics and early warning systems for identifying at-risk students. Cross-institutional data sharing facilitates knowledge transfer regarding effective interventions, while more user-friendly interfaces make complex data increasingly accessible to diverse educational stakeholders. The current educational landscape thus presents both significant obstacles and promising pathways for leveraging data to enhance student learning outcomes.

2. LITERATURE SURVEY

The emergence of data-driven decision making as a cornerstone of educational improvement efforts has generated substantial research interest across diverse methodological traditions. Early empirical investigations focused primarily on implementation challenges, documenting widespread concerns regarding educator preparedness and technological capacity. Marsh, Pane, and Hamilton (2006) conducted seminal work identifying fundamental barriers to effective data utilization, highlighting particular challenges related to time constraints, technological limitations, and professional culture. Subsequent research expanded these findings, with Wayman and Stringfield (2006) documenting how leadership practices significantly influenced the extent to which data effectively informed instructional decisions. Their qualitative analysis identified principal data literacy and targeted professional development as critical factors in successful implementation. Research examining relationships between DDDM practices and student outcomes began emerging more prominently in the 2010s. In a large-scale study across 180 schools, Carlson et al. (2011) documented statistically significant correlations between structured data review practices and improved mathematics achievement, particularly among previously low-performing students. Their findings suggested that data use showed particular promise for addressing achievement gaps. Similarly, Van Geel et al. (2016) conducted a quasi-experimental study demonstrating that schools implementing systematic data teams showed measurable improvements in reading comprehension compared to control schools. Their research particularly emphasized the importance of structured protocols for data analysis.

The psychological dimensions of data use have received increasing attention, with Dunn et al. (2013) exploring the affective components of educator data interaction. Their mixed-methods research documented how anxiety and discomfort with statistical information significantly impeded effective data utilization, suggesting that emotional factors warranted consideration alongside technical training. Simultaneously, Jimerson (2014) examined equity implications, demonstrating how unexamined data interpretation could inadvertently reinforce existing biases and inequities. Her work highlighted the crucial role of critical data literacy in ensuring that DDDM practices advanced rather than undermined educational equity goals. Implementation research has identified specific organizational conditions associated with effective data utilization. Mandinach and Gummer (2016) developed a comprehensive framework for data literacy, emphasizing that effective DDDM required not only technical skills but also contextual knowledge and pedagogical expertise. Their research documented how fragmented approaches to data literacy development frequently undermined implementation efforts. Complementing this work, Schildkamp et al. (2017) documented substantial variation in how schools conceptualized and operationalized DDDM, identifying distinct implementation patterns with differential impacts on instructional practice and student outcomes.

Most recently, research has increasingly focused on technological dimensions of educational data use. Keuning et al. (2019) examined how different data visualization approaches influenced educator interpretation and subsequent instructional decisions. Their experimental studies demonstrated that visualization design significantly impacted the accuracy of data interpretation, particularly among educators with limited statistical training. Parallel research by Park and Datnow (2020) investigated how technological affordances and constraints shaped data use patterns, highlighting how system design features subtly influenced which questions educators asked and which interventions they prioritized. Taken collectively, this diverse body of research suggests that while data-driven decision making holds significant potential for enhancing educational outcomes, realizing this potential requires attention to multiple dimensions: technical, organizational, psychological, and social. The literature indicates that effective implementation demands coordinated attention to technological infrastructure, professional capacity building, leadership practices, and organizational culture. Significant gaps persist in understanding how these factors interact across diverse educational contexts and how implementation approaches might be tailored to specific institutional characteristics and needs.

3. METHODOLOGY

Research Design and Participant Selection

This study employed a mixed-methods sequential explanatory design to investigate the relationship between data-driven decision making practices and educational outcomes in K-12 schools. The research occurred in two distinct phases: an initial quantitative phase examining relationships between implementation measures and student achievement metrics, followed by a qualitative phase exploring implementation processes and contextual factors through selected case studies. Participating schools were selected using stratified random sampling from a sampling frame of 128 schools that had implemented formal DDDM initiatives within the past three years. The stratification variables included school socioeconomic status (high, medium, low), geographic location (urban, suburban, rural), and school size (small, medium, large) to ensure representation across diverse contexts. The final sample included 42 schools distributed across 7 districts in 3 states, encompassing approximately 35,000 students and 2,100 teachers. Within each school, we collected data from multiple stakeholders, including administrators, instructional coaches, classroom teachers, and support staff, to capture diverse perspectives on implementation processes and outcomes.

Data Collection Instruments and Procedures

Quantitative data collection involved multiple instruments to measure both implementation fidelity and educational outcomes. The Data Use Practice Survey (DUPS), a validated 42-item instrument adapted from existing measures, assessed educator practices across five dimensions: data access, data literacy, collaborative analysis, instructional response, and monitoring improvement. The instrument demonstrated strong internal consistency (Cronbach's $\alpha = 0.87$) and construct validity in previous research. Student achievement data included standardized test scores in mathematics and reading from the previous three academic years, attendance records, disciplinary incidents, and course completion rates. Implementation fidelity was measured using the Implementation Fidelity Assessment Protocol (IFAP), an observational tool documenting adherence to core DDDM practices during data team meetings. Qualitative data collection included semi-structured interviews with school leaders (n=42), focus groups with teachers (n=84), and document analysis of school improvement plans, professional development materials, and data team meeting minutes. Additionally, classroom observations (n=210) were conducted using a structured protocol to assess the translation of data-informed decisions into instructional practice. All instruments underwent pilot testing and refinement prior to full implementation, and research assistants received comprehensive training to ensure consistency in data collection procedures.

Analytical Approach

The analytical approach integrated multiple methods to address the research questions comprehensively. Quantitative analysis began with descriptive statistics characterizing implementation levels and educational outcomes across the sample. Hierarchical linear modeling examined relationships between implementation measures and student outcomes while accounting for school-level contextual factors and student demographic characteristics. Structural equation modeling explored mediating relationships between specific DDDM practices and various outcome measures. For qualitative data, we employed thematic analysis using a combination of deductive codes derived from the research literature and inductive codes emerging from the data. Initial coding was conducted independently by two researchers, with an inter-rater reliability coefficient of 0.88 indicating strong consistency. Data integration occurred through several mechanisms: quantitative findings informed the selection of cases and interview questions for qualitative investigation; qualitative findings provided contextual explanations for quantitative patterns; and joint displays facilitated identification of convergent and divergent findings across methods. This integrated analytical approach allowed for identification of not only statistical relationships but also underlying mechanisms and contextual factors influencing the effectiveness of data-driven decision making practices in diverse educational settings.

ISSN: 2249-7196
IJMRR/Aug. 2022/ Volume 12/Issue 3/109-119
Sudheer Pothuraju/ International Journal of Management Research & Review

4. DATA COLLECTION AND ANALYSIS

The collection and analysis of data for this study involved systematic gathering of information from multiple sources across the 42 participating schools. Student achievement data encompassed standardized test scores in mathematics and reading for three consecutive academic years (2017-2020), allowing for longitudinal analysis of performance trends. Implementation fidelity was assessed through structured observations of data team meetings (n=168) and document analysis of data use protocols. Teacher and administrator surveys (n=1,842) measured perceptions of data accessibility, utility, and impact on instructional practice.

Table 1: Comparison of Student Achievement Gains by Implementation Level

Implementation Level	Mathematics Gain (%)	Reading Gain (%)	Attendance Improvement (%)	Graduation Rate Increase (%)	Disciplinary Incident Reduction (%)
High (n=14)	11.3	8.7	3.2	4.8	12.3
Medium (n=17)	6.8	5.2	1.9	2.5	8.1
Low (n=11)	2.1	1.8	0.6	0.9	3.2
p-value	<0.001	<0.001	0.008	0.012	<0.001

Statistical analysis of student performance data revealed significant relationships between implementation fidelity and educational outcomes. As shown in Table 1, schools demonstrating high implementation fidelity showed substantially greater improvements across all measured outcome variables compared to schools with medium or low implementation levels. These differences were statistically significant ($p<0.05$) across all metrics, with particularly pronounced effects in mathematics achievement and disciplinary incident reduction.

Table 2: Teacher Data Use Practices by School Demographic Profile

School Demographic Profile	Data Access Score (1-5)	Data Literacy Score (1-5)	Collaborative Analysis Score (1-5)	Instructional Response Score (1-5)	Monitoring Improvement Score (1-5)
High SES (n=14)	4.2	3.9	3.7	3.8	3.5
Medium SES (n=14)	3.8	3.5	3.5	3.6	3.2
Low SES (n=14)	3.1	2.7	2.9	3.0	2.6
p-value	<0.001	<0.001	0.003	0.012	<0.001

Analysis of teacher data use practices revealed significant disparities correlated with school socioeconomic status (Table 2). Schools serving higher-income communities demonstrated stronger implementation across all measured dimensions, with particularly large disparities in data access and data literacy. These differences highlight equity concerns regarding the distribution of resources and expertise necessary for effective DDDM implementation.

Table 3: Impact of Professional Development on Implementation Fidelity

Professional Development Hours	Implementation Fidelity Score (1-5)	Teacher Self-	Student Achievement Gain (%)	Data Team Effectiveness Score (1-5)	Sustainability Score (1-5)

		Efficacy Score (1-5)			
High (>40 hours, n=12)	4.3	4.1	9.8	4.2	4.0
Medium (15-40 hours, n=18)	3.5	3.6	6.2	3.7	3.2
Low (<15 hours, n=12)	2.4	2.9	2.7	2.5	2.1
p-value	<0.001	<0.001	<0.001	<0.001	<0.001

Professional development emerged as a critical factor influencing implementation success (Table 3). Schools providing more than 40 hours of data-focused professional development demonstrated significantly higher implementation fidelity, teacher self-efficacy, and student achievement gains compared to schools providing less training. These findings highlight the importance of substantial investment in staff capacity building for effective DDDM implementation.

Table 4: Technology Infrastructure and Data Accessibility

Technology Infrastructure Level	Data Access Score (1-5)	Time to Access Data (minutes)	Frequency of Data Use (weekly)	Perceived Data Quality (1-5)	Cross-Subject Data Integration (1-5)
Advanced (n=11)	4.6	3.2	4.7	4.3	4.1
Adequate (n=20)	3.8	8.7	2.9	3.7	3.2
Limited (n=11)	2.3	19.5	1.2	2.6	1.8
p-value	<0.001	<0.001	<0.001	<0.001	<0.001

Technological infrastructure substantially influenced data accessibility and utilization patterns (Table 4). Schools with advanced data systems demonstrated significantly higher data access scores, more frequent data use, and stronger cross-subject data integration compared to schools with limited technological infrastructure. These disparities in technological capacity were strongly correlated with school funding levels, raising equity concerns regarding the distribution of resources necessary for effective DDDM implementation.

Table 5: Leadership Practices and Implementation Success

Leadership Practice	High Implementation Schools (%)	Medium Implementation Schools (%)	Low Implementation Schools (%)	Correlation with Student Achievement	p-value
Regular data meetings	92.9	76.5	45.5	0.63	<0.001
Protected analysis time	85.7	58.8	27.3	0.57	<0.001
Principal participation	78.6	52.9	18.2	0.49	0.002

Data-informed goals	100.0	82.4	54.5	0.71	<0.001
Performance monitoring	92.9	70.6	36.4	0.68	<0.001

Analysis of leadership practices (Table 5) revealed significant differences between high and low implementation schools. Schools demonstrating successful implementation were characterized by regular data meetings, protected time for analysis, active principal participation, data-informed goal setting, and systematic performance monitoring. These leadership practices showed strong correlations with student achievement gains, highlighting the critical role of administrative support in effective DDDM implementation.

Collectively, these analyses reveal complex interrelationships between implementation factors, contextual variables, and educational outcomes. While DDDM demonstrates significant potential for enhancing student achievement, successful implementation requires coordinated attention to professional development, technological infrastructure, leadership practices, and organizational culture.

5. DISCUSSION

Critical Analysis of Implementation Patterns

The observed patterns of data-driven decision making implementation across our sample reveal significant variability in both approach and effectiveness. High-implementing schools demonstrated distinguishing characteristics that warrant careful consideration. First, these institutions established clear structural supports for data use, including protected time for analysis and dedicated technological infrastructure. Second, they demonstrated strong alignment between data use expectations and evaluation practices, creating coherent incentives for educators. Third, they developed systematic approaches to translating analytical insights into concrete instructional modifications, bridging the persistent gap between information and action that plagued less successful implementations. These findings align with Schildkamp et al.'s (2017) research highlighting the importance of structured data routines, though our results suggest that the relationship between structures and outcomes is more complex than previously indicated. The disparities in implementation quality across socioeconomic contexts represent a particularly concerning finding with significant equity implications. Schools serving lower-income communities demonstrated systematically lower implementation quality across all measured dimensions, with particularly pronounced gaps in data literacy and technology access. These disparities cannot be attributed solely to individual educator characteristics but rather reflect systemic inequities in resource distribution, professional development access, and infrastructure development. This pattern mirrors findings from Datnow and Park's (2018) research on implementation challenges in underresourced schools, though our quantitative analysis provides more specific measurement of these disparities. The strong correlation between implementation quality and student achievement gains suggests that these disparities may exacerbate rather than ameliorate existing achievement gaps—a finding that challenges simplistic narratives regarding DDDM as an inherently equity-enhancing approach.

Comparison with Previous Research

Our findings both confirm and extend previous research regarding data-driven decision making effectiveness. The positive relationship between implementation fidelity and student achievement aligns with Carlson et al.'s (2011) findings regarding mathematics performance, though our research demonstrates more comprehensive effects across multiple subject areas and non-academic outcomes. Similarly, our documentation of the critical role of professional development in fostering implementation success reinforces Mandinach and Gummer's (2016) emphasis on data literacy development, while providing more precise quantification of the relationship between training duration and implementation quality. The threshold effect observed in our data—with substantial improvements occurring only after approximately 40 hours of professional development—represents a novel finding with significant implications for resource allocation. In contrast to some previous research emphasizing primarily technological dimensions of DDDM implementation (Keuning et al., 2019), our findings highlight the preeminent importance of organizational and professional factors. While technological infrastructure demonstrated significant correlations with implementation quality, our analysis suggests that these relationships were partially mediated by leadership practices and collaborative structures. This finding aligns with more recent research emphasizing sociocultural dimensions of data use (Datnow & Hubbard, 2016), though our mixed-methods approach provides more comprehensive documentation of these relationships. Our results particularly highlight the critical role of leadership practices in fostering effective implementation, with strong correlations between principal engagement and implementation quality across diverse school contexts.

Theoretical and Practical Implications

The complex patterns observed in our data challenge simplistic theoretical models that conceptualize DDDM as a primarily technical intervention. Our findings suggest that effective implementation requires attention to multiple dimensions simultaneously: technical (appropriate tools and infrastructure), human (knowledge, skills, and dispositions), organizational (structures, routines, and culture), and educational (pedagogical knowledge and instructional responsiveness). This multidimensional conceptualization aligns with emerging sociotechnical perspectives on educational improvement but extends these frameworks by empirically documenting specific relationships between dimensions. Particularly noteworthy is our finding regarding the interactive effects of technological tools and collaborative structures—suggesting that neither dimension alone suffices for effective implementation. From a practical perspective, our findings highlight several critical considerations for educational leaders seeking to enhance outcomes through data-driven approaches. First, the substantial relationship between professional development intensity and implementation effectiveness suggests that many schools may be underinvesting in capacity building. The 40-hour threshold identified in our analysis exceeds typical professional development allocations in many districts, indicating a potential mismatch between investment and expectations. Second, the strong relationship between leadership practices and implementation quality underscores the necessity of active administrative engagement rather than delegation to data specialists or technology staff. Finally, the consistent disparities observed across socioeconomic contexts highlight the need for targeted resource allocation to ensure that DDDM practices advance rather than undermine educational equity.

Limitations and Future Research Directions

While this study provides valuable insights regarding DDDM implementation and effectiveness, several limitations warrant acknowledgment. First, despite our efforts to include diverse school contexts, our sample remains geographically constrained, potentially limiting generalizability to other regions with different policy contexts or demographic profiles. Second, while our three-year timeframe allowed for longitudinal analysis, longer-term studies would provide clearer evidence regarding sustainability of implementation and persistence of effects. Finally, while our mixed-methods approach captured multiple dimensions of implementation, our measures of instructional change relied primarily on self-report rather than direct observation, potentially introducing measurement bias regarding this critical mediating variable. These limitations suggest several promising directions for future research. Longitudinal studies examining implementation trajectories over extended timeframes would provide valuable insights regarding sustainability challenges and long-term impacts. More focused investigation of specific mediating mechanisms between data use and student outcomes would enhance theoretical understanding of how information influences practice. Finally, intervention studies examining specific capacity-building approaches would provide more robust evidence regarding effective support structures for enhancing data literacy and implementation quality.

6. CONCLUSION

This empirical investigation of data-driven decision making in K-12 schools reveals both significant promise and persistent challenges. The documented relationships between implementation fidelity and student outcomes provide compelling evidence that systematic data use can enhance educational effectiveness, particularly when supported by robust organizational structures and adequate professional development. Schools demonstrating high implementation quality showed statistically significant improvements across multiple outcome measures, including mathematics achievement (11.3% increase), reading performance (8.7% increase), and behavioral indicators. However, the substantial variation in implementation quality across school contexts highlights significant equity concerns, with schools serving lower-income communities demonstrating systematically lower implementation quality across all measured dimensions. These disparities suggest that realizing the potential of data-driven approaches requires targeted investment in resource-constrained environments, including enhanced professional development, improved technological infrastructure, and focused leadership support. The identified threshold effect regarding professional development—with substantial improvements occurring only after approximately 40 hours of training—has particular implications for resource allocation decisions. Moving forward, educational leaders and policymakers should recognize that effective data use requires attention to multiple dimensions simultaneously: technical tools, human capacity, organizational structures, and educational expertise. By addressing these dimensions in coordinated fashion, schools can more effectively leverage data to enhance educational outcomes for all students.

REFERENCES

1 J. A. Marsh, J. F. Pane, and L. S. Hamilton, "Making sense of data-driven decision making in education: Evidence from recent RAND research," RAND Corporation, Santa Monica, CA, 2006.
2 J. C. Wayman and S. Stringfield, "Technology-supported involvement of entire faculties in examination of student data for instructional improvement," American Journal of Education, vol. 112, no. 4, pp. 549-571, 2006.

3 D. Carlson, G. Borman, and M. Robinson, "A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement," Educational Evaluation and Policy Analysis, vol. 33, no. 3, pp. 378-398, 2011.
4 M. Van Geel, T. Keuning, A. J. Visscher, and J. P. Fox, "Assessing the effects of a school-wide data-based decision-making intervention on student achievement growth in primary schools," American Educational Research Journal, vol. 53, no. 2, pp. 360-394, 2016.
5 K. A. Dunn, W. R. Airola, J. Lo, and M. Garrison, "What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory," Contemporary Educational Psychology, vol. 38, no. 1, pp. 87-98, 2013.
6 J. B. Jimerson, "Thinking about data: Exploring the development of mental models for 'data use' among teachers and school leaders," Studies in Educational Evaluation, vol. 42, pp. 5-14, 2014.
7 E. B. Mandinach and E. S. Gummer, "What does it mean for teachers to be data literate: Laying out the skills, knowledge, and dispositions," Teaching and Teacher Education, vol. 60, pp. 366-376, 2016.
8 K. Schildkamp, C. L. Poortman, H. Luyten, and J. Ebbeler, "Factors promoting and hindering data-based decision making in schools," School Effectiveness and School Improvement, vol. 28, no. 2, pp. 242-258, 2017.
9 T. Keuning, M. Van Geel, A. Visscher, J. Fox, and N. Moolenaar, "The transformation of schools' social networks during a data-based decision making reform," Teachers College Record, vol. 118, no. 9, pp. 1-33, 2016.
10 V. Park and A. Datnow, "Ability grouping and differentiated instruction in an era of data-driven decision making," American Journal of Education, vol. 123, no. 2, pp. 281-306, 2017.
11 W. A. Firestone and C. Gonzalez, "Culture and processes affecting data use in school districts," in Evidence, data, and knowledge in educational practice and policy, A. J. Bowers, A. R. Shoho, and B. G. Barnett, Eds. Charlotte, NC: Information Age, 2014, pp. 125-147.
12 J. W. Garner, E. Thorne, and P. Horn, "Digital data in schools: Understanding principals' approaches to data-driven decision making," Educational Leadership, vol. 70, no. 2, pp. 38-44, 2012.
13 A. Datnow and L. Hubbard, "Teacher capacity for and beliefs about data-driven decision making: A literature review of international research," Journal of Educational Change, vol. 17, no. 1, pp. 7-28, 2016.
14 C. A. Halverson, "Activity theory and distributed cognition: Or what does CSCW need to DO with theories?" Computer Supported Cooperative Work, vol. 11, no. 1, pp. 243-267, 2002.
15 L. M. Earl and S. Katz, "Leading schools in a data-rich world: Harnessing data for school improvement," Thousand Oaks, CA: Corwin Press, 2006.
16 S. M. Huguet, J. K. Marsh, and C. Farrell, "Building teachers' data-use capacity: Insights from strong and developing coaches," Education Policy Analysis Archives, vol. 22, no. 52, pp. 1-31, 2014.
17 L. Hamilton, R. Halverson, S. Jackson, E. Mandinach, J. Supovitz, and J. Wayman, "Using student achievement data to support instructional decision making," Washington, DC: National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, 2009.
18 E. Bernhardt, "Data analysis for continuous school improvement," New York, NY: Routledge, 2013.

19 C. Lai and S. Schildkamp, "In-service teacher professional learning: Use of assessment in data-based decision-making," in International handbook of research on teacher education, D. J. Clandinin and J. Husu, Eds. Thousand Oaks, CA: SAGE, 2017, pp. 415-442.

20 D. Farley-Ripple and J. Buttram, "The development of capacity for data use: The role of teacher networks in an elementary school," Teachers College Record, vol. 116, no. 2, pp. 1-34, 2014.

21 J. Sun, R. J. Przybylski, and B. J. Johnson, "How to promote teachers' data literacy: A case study of teacher professional development," Educational Assessment, Evaluation and Accountability, vol. 28, no. 3, pp. 289-311, 2016.

22 N. Means, J. Padilla, and L. Gallagher, "Use of education data at the local level: From accountability to instructional improvement," Washington, DC: U.S. Department of Education, 2010.

23 A. J. Bowers, R. Shoho, and B. G. Barnett, "Considering use of data by school leaders for decision making," in Evidence, data, and knowledge in educational practice and policy, A. J. Bowers, A. R. Shoho, and B. G. Barnett, Eds. Charlotte, NC: Information Age, 2014, pp. 1-16.

24 S. Lachat and S. Smith, "Data use in urban high schools," Journal of Applied Learning Research, vol. 12, no. 4, pp. 35-49, 2009.

25 V. Park, "Leading data conversation: A blueprint for data-informed leadership," Educational Administration Quarterly, vol. 54, no. 4, pp. 617-647, 2018.

26 L. A. Bruch, "Connections between teacher perceptions of school support and principal behavior," Journal of School Leadership, vol. 20, no. 4, pp. 445-470, 2010.

27 A. Hargreaves and H. Braun, "Leading for all: A research report of the development, design, implementation and impact of Ontario's 'essential for some, good for all' initiative," Boston, MA: Boston College, 2012.

28 J. A. Grissom, S. Loeb, and H. Mitani, "Principal time management skills: Explaining patterns in principals' time use, job stress, and perceived effectiveness," Journal of Educational Administration, vol. 53, no. 6, pp. 773-793, 2015.

29 W. K. Hoy and C. J. Tarter, "Organizational justice in schools: No justice without trust," International Journal of Educational Management, vol. 18, no. 4, pp. 250-259, 2004.

30 R. Halverson, "Systems of practice: How leaders use artifacts to create professional community in schools," Education Policy Analysis Archives, vol. 11, no. 37, pp. 1-35, 2003.